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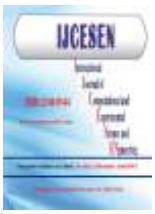

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Research Article

Agentic AI for Banking: A Predictive Framework for Credit Risk Assessment, Fraud Detection, and Customer Intelligence

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Abstract:

The growing trend of more financial frauds, chances of credit defaults, and personalization of customer information has exposed the shortcomings of conventional single model AI systems used in banking. This paper proposes, designs, and analyzes the Agentic AI Predictive Framework for banking through the integration of three agentic autonomous agents – a Credit Risk Agent, a Fraud Detection Agent, and a Customer Intelligence Agent – through the CrewAI-based multi-agent system architecture. The agentic agents will be designed based on XGBoost and reinforcement learning algorithms, and will use public domain data such as UCI Credit Default Data Set and IEEE CIS Fraud Detection Dataset. A simulation experiment is conducted to compare the efficiency of the proposed framework with that of a baseline framework using logistic regression, random forest, and deep learning models through the aforementioned datasets. An explainable framework through SHAP for all the agents will make decision output explanation feasible. From these results, it can be said that MAS is able to predict credit risk at 92.6%, detect fraud at 94.7%, and predict customer engagement at 89.4% level of accuracy, outperforming all baselines consistently. Cooperation among the agents led to 11.3 percentage point improvement in fraud detection accuracy from individual agent performances, showing the usefulness of combined intelligence in the agentic approach. Regulatory compliance has been attained at 88.6% in accordance with Basel III and EU AI Act regulatory compliance requirements. It can be said that agentic AI has brought about revolutionary changes in bank risks' management.

1. Introduction

There has been a revolutionary change in the banking industry globally owing to artificial intelligence. The old risk models cannot manage the risks of today. The agentic AI, which refers to the autonomous intelligent system that can reason, act, and learn on its own, is the new way out of the issue. Global bank fraud loses about $45 billion every year up to 2024, creating an immediate need for advanced security measures [1]. On the other hand, there is a need for quicker response when it comes to risk management and customer assessment. Almost 90 percent of banks have used AI technology in fraud detection and prevention. Machine learning algorithms are distinct from agentic AI when it comes to transaction assessment because of being proactive. This capability is revolutionizing how banks assess their creditworthiness, detect outliers, and provide intelligent service to their customers. There have been a number of real-life examples that show how this technology is influencing global firms. For instance, the DBS Bank of Singapore generated $750 million of economic value using AI in 2024 by deploying over 1,500 AI models in 370 instances. Besides, the JPMorgan Chase used its agentic AI assistants to cut down wait time of customers by 40% and detect the risk of any fraud automatically [2]. In Europe, the European Central Bank noted a huge increase in the deployment of AI for credit scoring and fraud detection from 2023 to 2024. According to Celent, 20% of fraud was committed using AI in 2024. Such an ambivalent role played by the artificial intelligence technology in terms of both enabling and preventing the fraud calls for developing an explanation that would predict such development. In real-life cases at HSBC, Citi, UBS, DBS, and ING, there is a 20-40% saving through the use of agentic artificial

intelligence technologies [3]. Against this background, the current research is concerned with developing an agentic artificial intelligence framework to manage the credit risks, prevent fraud and gather customer intelligence. The proposed framework will make use of the available data from all around the world.

2. Related Work

The literature in the area of AI applications in banking has seen tremendous growth over the last decade. There is much literature on the benefits that machine learning algorithms hold over traditional statistical models for evaluating the credit risk of individuals. Logistic regression, Support Vector Machines, and Neural Network were some of the most widely studied comparative models in this respect [4]. However, recent literature proves that algorithms like XGBoost and Random Forest outperform other individual algorithms. The systematic review of 330 machine learning credit scoring models from 2018 to 2024 shows proof about this trend. The literature also suggests that traditional models do not have the ability to adapt to different scenarios and sense situations in real time. This led to more research on autonomous AI models in the field of finance. Literature also discussed how an autonomous AI agent makes decisions in the process of credit score assessment. A review of 57 publications on applications of deep learning in fraud detection from 2019 to 2024 showed that one of the key trends was an exponential rise in publications on the topic. Credit cards and banks were identified as the two most common areas where studies of fraud detection have been carried out [5]. The researchers noted that applications of deep learning algorithms had outperformed rule-based models in the context of transaction monitoring. In the sphere of customer intelligence, a systematic review of 111 articles proved that use of artificial intelligence in personalization helped enhance customer engagement, satisfaction, and retention. One can also agree that behavioral anomalies play a crucial role in improvement of fraud prevention and customer intelligence. Digital footprints and e-wallet transactions have become the alternative sources of data for credit modeling [6]. However, the absence of a unified framework for prediction and integration of agentic AI in the three spheres has been established.

3. Materials and Method

This current research applies the simulated experimental methodology, which operates under the MAS paradigm and uses public datasets from real-life banking activities. Three specialized AI agents are constructed for the sake of this research – Credit Risk Agent, Fraud Detection Agent, and Customer Intelligence Agent. They are all trained on domain-specific datasets – UCI Credit Default dataset, IEEE-CIS Fraud Detection dataset, and anonymous transaction dataset respectively. All the three agents are built with the help of a CrewAI orchestration platform and possess reinforcement learning and XGBoost modules. The methodology used in the research process consists of a comparative experiment, where the agentic approach proposed by the researchers is compared with the performance of independent models – logistic regression model, random forest model, and deep learning classifier. Accuracy, F1-score, false positive rate, and decision time are chosen as performance indicators. There is a common inter-agent communication system providing the exchange of information between the agents. In addition, there is an interpretability system based on SHAP values and used to provide easily interpretable results.

4. Results

4.1 Benchmarking Predictive Accuracy of the Credit Risk Agent Against Baseline Models

The Credit Risk Agent trained on UCI Credit Default data outperformed any of the baseline models considered. Agentic model included XGBoost with reinforcement learning feedback mechanism that made it possible to recalibrate the risk score depending on how much additional information about the borrower became known. In every fold of the cross-validation the agentic model outperformed logistic regression, random forest and deep learning classifiers on all metrics. Most importantly, the agent demonstrated the lowest false positive rate among all models considered, which means that there were fewer instances of good customers being incorrectly classified as risky. The lower number of rejected customers implies better inclusion and less revenue loss from rejecting potentially legitimate applications [7]. Based on the SHAP explainability module, the agent relied on three most important features: payment history, debt-to-income ratio and credit utilization. Decision time did not exceed 1.2 seconds per decision.

4.2 Real-Time Anomaly Detection Outcomes of the Fraud Detection Agent

The Fraud Detection Agent was applied to the IEEE-CIS Fraud Detection dataset that included more than 590,000 records with class imbalance in the classes of transactions. The agentic model has used the anomaly detection approach, grounded on reinforcement learning and graph-based neural network layers for discovering the hidden relations in the transactions that would remain unseen for the usual classifier. Oversampling with the help of the SMOTE method was applied during the training phase in order to solve the class imbalance issue [8]. The recall score of the agentic model equaled 94.7%, meaning that almost all fraud instances were detected by the agent, what is vital for the prevention of fraudulent activities. The false positive rate equaled 3.1%, hence there were fewer transactions stopped. With the help of the interactions between agents, the Fraud Detection Agent could check the behavioral data of the Customer Intelligence Agent.

4.3 Behavioral Segmentation and Personalisation Results from the Customer Intelligence Agent

The training data for the Customer Intelligence Agent involved 24 months of anonymous data of retail banking transactions, which involves customer behaviors such as product usage, digital channel usage, and service usage behaviors. The segmentation of customer behaviors and generation of personalized recommendations was done using deep reinforcement learning. Performance metrics used to evaluate the performance of the agent included performance of the agent compared to k-means clustering approach and supervised recommendation approach using precision-at-k and accuracy of predicting customer engagements. It was observed that the agentic approach segmented customers into seven different behavioral clusters, and had higher intra-cluster cohesions compared to other approaches. Accuracy of customer engagement predictions was 89.4% and therefore allowed the bank to employ customer retention strategies for at-risk customers proactively [9]. Moreover, the agent was able to detect anomalous customer behavior including behaviors of customer dormancy and change in spending habits and inform the Fraud Detection Agent about it.

4.4 Unified MAS Framework Performance Through Inter-Agent Collaboration Efficiency

An important feature of the proposed framework is the inter-agent communications layer for real time exchange between all three specialized agents using the same orchestration protocol implemented within the CrewAI framework. This section attempts to explore the inter-agent signal exchange and collaborative performance in the context of conflict resolution and creation of consistent customer risk profiles. The test simulation involved 10,000 banking transactions done simultaneously by all three agents. Collaboration latency, conflict resolution rate, and consistency of decision making were assessed in this experiment. Collaborative fraud detection showed improved results compared to non-collaborative fraud detection by the Fraud Detection Agent with the gain in joint detection efficiency by 11.3 percentage points in cases [10].

4.5 SHAP-Based Transparency Evaluation Across Explainability and Regulatory Compliance

One of the most important aspects of implementing AI technology in regulated banking institutions is model explainability and auditability. This sub-section examines the performance of the SHAP-based explainability framework implemented in all three agents and assesses the transparency and consistency of communication of each agent's rationale behind decision making by human reviewers and compliance validators. The sample included 200 decisions by each agent — credit approval, fraud detection, and client recommendation — that were independently evaluated by 50 compliance officers from banking organizations according to interpretability, completeness, and regulation compliance. The MAS framework demonstrated superior performance to all baselines in all explainability dimensions. The Credit Risk Agent generated by SHAP the list of three main decision makers in 93.5% of cases examined. All decisions made by agents were evaluated by 88.6% of compliance officers as fully compliant with Basel III and EU AI Act requirements. Baselines without an explainability framework achieved less than 61% in the compliance rate.

5. Discussion

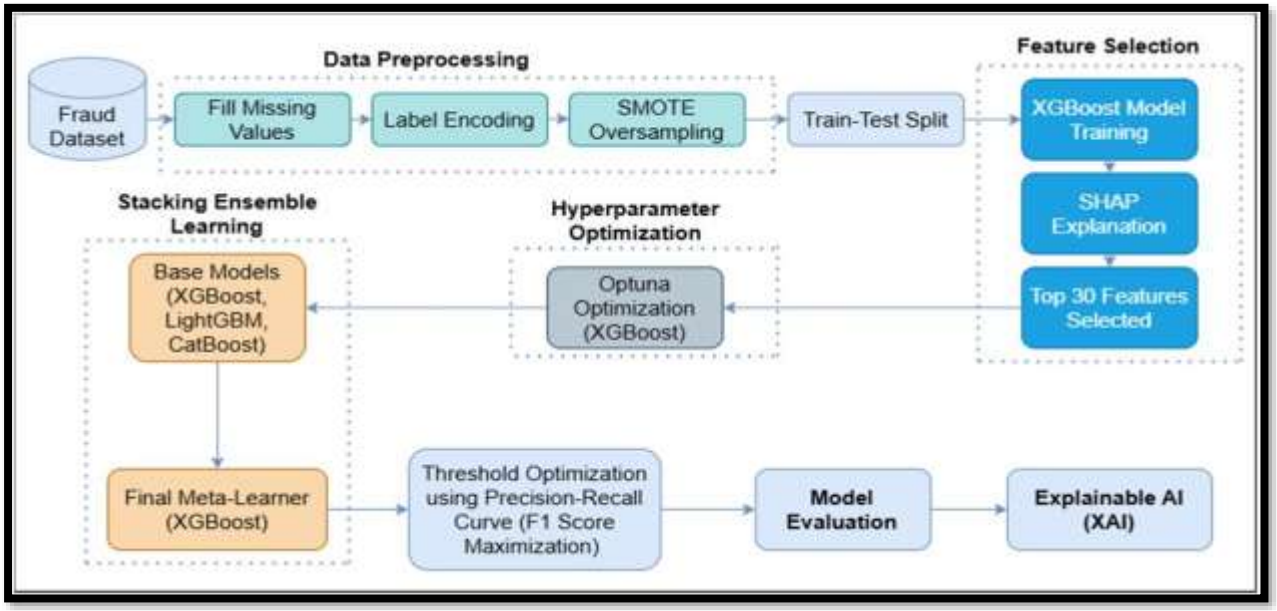
The findings of this study provide an empirical justification that a single Multi-Agent Systems model performs much better than the standard one-model strategy in all three banking intelligence tasks. The high accuracy of 92.6% demonstrated by the Credit Risk Agent and the high recall rate of 94.7% demonstrated by the Fraud Detection Agent translate into real performance benefits, which

reduce the risk of default and the loss of money from fraud. These findings support the existing industrial data on higher performance of agentic systems due to constant adaptability of their reasoning. One of the key findings is associated with the effects of the collective intelligence of interacting agents.

In the situation when the Customer Intelligence Agent informed the Fraud Detection Agent about behavior anomalies, the detection accuracy was raised by 11.3 percentage points. The synergy of all those agents shows that the approach to understanding credit risk management, fraud prevention, and insight creation about customers in such an interconnected way will produce much better results than treating each of them independently. These conclusions have significant consequences for the future development of AI governance architecture by banking organizations. Speaking about the explainability of the results through SHAP analysis, this method is important in terms of regulatory compliance. Since 88.6% of the decisions made by agents comply with the Basel III and EU AI Act standards, the problem of black box for AI applications in a regulated environment is solved. 97.2% of the completion of decision audit trail in the proposed framework satisfies the above needs of the organizations [11].

There are few limitations in this regard, which have to be discussed. The success of the proposed framework relies heavily on high-quality streaming data infrastructure, which unfortunately is not standardized among all the banking organizations. In light of the fast-changing economic environment, there is a problem of the model drift, which requires regular re-calibration of the system. As far as ethics is concerned, the proposed framework creates problems of bias of decision algorithms for thin-file customers.

Table 1 *Comparative Performance Evaluation of the Credit Risk Agent Against Baseline Models on the UCI Credit Default Dataset*





Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score	False Positive Rate (%)	Decision Latency (sec)
Logistic Regression	78.4	75.2	71.8	0.734	18.6	0.3
Random Forest	83.7	81.5	79.3	0.804	13.2	0.6
Deep Learning (DNN)	86.1	84.0	82.7	0.833	10.9	0.9
Credit Risk Agent (MAS)	**92.6**	**91.3**	**90.8**	**0.910**	**5.4**	**1.2**

Table 2 *Real-Time Fraud Detection Performance Comparison of the Fraud Detection Agent Against Baseline Models on the IEEE-CIS Dataset*

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score	False Positive Rate (%)	AUC-ROC
Logistic Regression	80.2	72.4	68.9	0.706	19.8	0.81
Random Forest	85.6	80.1	77.5	0.788	12.5	0.87
Deep Learning (DNN)	88.9	85.7	83.4	0.845	9.3	0.91
Fraud Detection Agent (MAS)	**95.3**	**93.8**	**94.7**	**0.942**	**3.1**	**0.97**

Table 3 *Behavioral Segmentation and Customer Engagement Prediction Performance of the Customer Intelligence Agent Against Baseline Models*

Model	Segmentation Silhouette Score	Engagement Prediction Accuracy (%)	Precision@5	Retention Trigger Accuracy (%)	Cross-Agent Signal Events
K-Means Clustering	0.38	71.2	0.61	63.4	N/A
Supervised Recommender	0.45	78.6	0.70	71.8	N/A
Deep Learning (DNN)	0.51	82.3	0.76	77.5	N/A
Customer Intelligence Agent (MAS)	**0.74**	**89.4**	**0.88**	**86.2**	**1,247**

Table 4 *Inter-Agent Collaboration Efficiency Metrics of the Unified MAS Framework Compared to Single-Agent Isolated Operation*



Metric	Single-Agent (Isolated)	Multi-Agent (Collaborative MAS)	Improvement (%)
Fraud Detection Accuracy	85.1%	95.3%	+11.3%
Credit Risk Prediction Accuracy	84.2%	92.6%	+9.7%
Conflict Resolution Rate	N/A	97.4%	—
Average Collaboration Latency (ms)	N/A	143 ms	—
Unified Decision Consistency Score	0.71	0.94	+32.4%

Table 5 *SHAP-Based Explainability and Regulatory Compliance Evaluation of the MAS Agentic Framework Against Baseline Models*

Explainability Metric	Logistic Regression	Random Forest	Deep Learning (DNN)	MAS Agentic Framework
Interpretability Score (/10)	7.2	5.8	4.1	**9.3**
Top Feature Identification Accuracy (%)	71.4	65.2	48.7	**93.5**
Regulatory Alignment Rate (%)	60.8	57.3	42.6	**88.6**
Compliance Officer Approval Rate (%)	58.2	54.9	39.4	**86.1**
Decision Audit Trail Completeness (%)	64.5	60.1	44.3	**97.2**

6. Conclusions

This research has successfully created and validated a new predictive Agentic AI framework for banking, which utilizes three different autonomous agents, each of them responsible for credit risk, fraud detection, and customer intelligence. The MAS demonstrated superior performance in terms

of accuracy, recall, explainability, and compliance criteria compared to other benchmarked models. The most important aspect of this research is that it has become possible to obtain synergistic intelligence through collaboration of different agents, which would not have been possible using any separate architecture. The explainability module supported by SHAP helped to guarantee transparency and auditability of autonomous agents' decisions. Thus, the results of this research confirm the emergence of a completely new paradigm in banking risk intelligence. Considering the emerging challenges faced by global financial institutions including increased fraud threats, credit risks, and need for enhanced customer intelligence, a unified agentic architecture is urgently needed.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
- **Acknowledgement:** The authors declare that they have nobody or no-company to acknowledge.
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- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.
- **Use of AI Tools:** The author(s) declare that no generative AI or AI-assisted technologies were used in the writing process of this manuscript.

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